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Abstract

In this paper we examine the predictions of the non-scale endogenous growth theories that an increase in the share of researchers in labour leads to an increase in innovation and innovation raises per capita output. Using panel data from 41 OECD and non-OECD countries, we show that an increase in the share of researchers in labour increases innovation only in the large market OECD countries. In addition, innovation raises per labour GDP in the high income OECD countries only, while raising it in all non-OECD countries, except for the low income countries. These results provide strong support for the non-scale endogenous growth theories.

JEL Classification Numbers: O30, O31, O33, O47.

Keywords: innovation, R&D, patents, output, panel data, generalized methods of moments (GMM).

I. Introduction

After more than a decade of empirical work on the first generation endogenous growth theories, it has become widely accepted that the scale effect prediction of these models are not consistent with the growth patterns of world economies.[1] Motivated by these empirical studies, Young (1998), Aghion and Howitt (1998) and Dinopoulos and Thompson (2000) have developed the non-scale endogenous growth theories that remove the scale effect while retaining the long-term growth prediction of endogenous growth models.[2] There have been numerous micro level analyses that confirm the

[1] The first generation endogenous growth models of Romer (1986; 1990), Grossman and Helpman (1991) and Aghion and Howitt (1992), R/GH/AH hereinafter, have pioneered the endogenous growth literature by placing the endogenous technological change at the centre of growth theories to explain the long-term growth rate of output. The central assumptions of the R/GH/AH model are that technological innovation is determined by the knowledge stock and human capital engaged in R&D, and it has unit elasticity in terms of both inputs. However, the assumption of these models that innovation has unit elasticity in terms of human capital in the R&D sector leads to the scale effect prediction that long term growth rate of output is determined by the level of population. This prediction has been rejected by Jones (1995b), who found that there was no relationship between TFP and the number of scientists and engineers in France, Germany, Japan and the U.S.

[2] The second generation non-scale endogenous growth models of Young (1998), Aghion and Howitt (1998) and Dinopoulos and Thompson (2000), Y/AH/DT hereinafter, remove the scale effect by replacing the human capital variable in the innovation function of R/GH/AH with the ratio of human capital to total labour force, or with the GDP share of R&D investment (R&D intensity). They argue that, as the numbers of new products and sectors increase over time, the R&D investment has to increase just to keep the innovation rate constant for each sector. Thus, they suggest that the fraction of

predictions of the non-scale endogenous growth theories for the U.S. economy, such as Griliches (1986), Jaffe (1988), Aghion and Howitt (1998) and Zachariadis (2003). Recent sector level cross-country analyses also support these models, Griffith, Redding and Reenen (2004) and Meliciani (2000). However, the macro level analyses of the non-scale endogenous growth models are limited to a few studies that cover only a small number of OECD countries. For example, Zachariadis (2004), Frantzen (2000) and Gong, Greiner, and Semmler (2004) examine the relationship between total factor productivity (TFP) and R&D intensity using data from OECD countries and find a positive relationship between these variables.

The present study differs from the existing empirical analyses in that it employs macro level patent and R&D data for 26 OECD and 15 non-OECD countries to examine the non-scale endogenous growth theories. In particular, we look at the following predictions of these models: an increase in the share of researchers in labour force increases innovation, and innovation raises per capita output. In addition to the main variables of the non-scale endogenous growth models, we also include in our analysis international knowledge spillovers, overall human capital capacity of countries and the U.S. trade share of GDP. As indicated by Coe, Helpman and Hoffmaister (1995), Lichtenberg and Potterie (1998) and Savvides and Zachariadis (2003), international knowledge spillovers are an important determinant of the TFP and output growth. These studies show that the more open the countries are to trade, the more likely it is

R&D in the total economy should be used to test the R&D models rather than the absolute value of R&D investment, or the absolute number of scientists and engineers.

that they will benefit from foreign R&D. We also incorporate the U.S. trade share of GDP into our analysis to capture the effect of knowledge spillovers from the U.S. on innovation, and to control for the effect of economic alliance with the U.S. on patent applications made in the U.S.

The findings of our analysis suggest that an increase in the fraction of researchers in labour increases innovation only in the large market OECD countries that include the G7. In addition, innovation raises per labour GDP in the high income OECD countries only, while raising it in all non-OECD countries except for the low income countries. Moreover, the impact of international knowledge spillovers on innovation seems to be significant only in the large market OECD countries, while the effect of openness to trade on per labour GDP is positive in the majority of the OECD and non-OECD countries.

This study extends the earlier research program in several dimensions. Firstly, it employs aggregate patent data as well as R&D data to examine the non-scale endogenous growth theories. Although patent data have been widely used in the micro level studies, to the best of our knowledge, only Porter and Stern (2000) employ aggregate patent and R&D data to examine the endogenous growth theories.[3] Our

[3] Porter and Stern (2000) employ data on patents and the number of scientists and engineers for 16 OECD countries to estimate the knowledge and output production functions using OLS and fixed effects regression techniques. Their findings show that both knowledge stock and the number of scientists and engineers increase the ideas production function, and that there is a positive relationship

study differs from Porter and Stern (2000) in that it is based on the non-scale endogenous growth models and it uses patent flows instead of patent stock in the estimation of the production function, as the former is shown to be a better proxy for innovation, Kortum (1993). Secondly, different from the previous literature that mainly employs data from OECD countries, this analysis covers 26 OECD and 15 non-OECD countries. This allows us to compare the results across developed and developing countries. Finally, we employ both the fixed effects and generalized methods of moments (GMM) dynamic panel data analyses to increase the robustness of our findings.

The remainder of the paper is organised as follows: the next section introduces the model, section three describes the data, section four presents the empirical analysis and results and section five concludes.

II. MODEL

The first generation endogenous growth theories (R/GH/AH) consist of three sectors: R&D, intermediate goods and final goods sectors. The R&D sector produces new designs using knowledge stock and human capital. It then sells these designs to the intermediate goods sector that produces new capital goods for the final output sector. The final output sector produces single consumption goods by using physical and

between patent stock and aggregate output. They also find that the foreign knowledge stock has a negative effect on ideas production function.

human capital, labour and technological innovation (new ideas). Both the R&D and final output sectors are perfectly competitive, while the intermediate goods sector is monopolistically competitive. The aggregate production is described by the standard Cobb-Douglas function:

$$Y(t) = A(t)X(t)^{\alpha} H_Y(t)^{\beta} L_Y(t)^{1-\alpha-\beta}, \tag{1}$$

where, Y, A, X, H_Y and L_Y are final output, technological innovation, physical capital that embodies both existing and new capital, human capital and labour employed in the final output sector, respectively. Technological innovation is created according to the following functional form:

$$\dot{A}(t) = A(t)\lambda H_A(t), \tag{2}$$

where A is the knowledge stock and H_A is human capital employed in the R&D sector. The assumption that innovation is linear in knowledge stock is crucial for the long-term growth rate of output. Models in the form of (2), where innovation has unit elasticity with respect to both knowledge stock and human capital in the R&D sectors, yield a steady state growth rate that depends on the level of population. However, the scale effect of these models has been rejected by Jones (1995b) and many other studies. A modified version of equation (2), which removes the scale effect while retaining the long-term growth prediction, was developed by Aghion and Howitt (1998), Young (1998) and Dinopoulas and Thompson (2000): [4]

$$\dot{A}(t) = A(t)^{\phi} \gamma \left(\frac{H_A(t)}{L(t)} \right)^{\psi} \quad \phi = 1, \tag{3}$$

where $\dot{A}$, *A, H,* and *L* are technological innovation, knowledge stock, human capital in the R&D sectors and labour force, respectively; ψ measures instantaneous returns to scale in knowledge creation and γ is equal to $\lambda/k^{\psi}>0$, where k is a constant. This specification of the innovation function leads to a balanced growth rate of per capita output that depends on the saving rate of physical and human capital as well as the growth rate of population. Equation (3) takes into account the opposite effects of an increase in population on the rate of innovation. On the one hand, an increase in the growth rate of population increases the rate of innovation, by increasing the human capital in the R&D sector, expanding the market for intermediate capital goods, raising the present value of the flow of profits and making investment in capital goods designs more attractive. On the other hand, more rapid population growth reduces the capital output ratio, and increases the interest rate through the standard neo-classical

[4] Equation (3) is based on Dinopoulos and Thompson (2000). The only difference between the innovation function in Dinopoulos and Thompson (2000) and Aghion and Howitt (1998) and Young (1998) is that DT uses the ratio of human capital to population, while Y/AH uses the GDP share of R&D investment.

mechanism, which is a deterrent to knowledge creation. In addition, a large number of people means more competition for the creation of similar ideas, making it more difficult to innovate, Jones (1995a). Therefore, the final effect of an increase in population on innovation depends on which of these opposing effects are dominant.[5] After describing the data in the next section, in section four, we estimate equation (1) and (3) to examine the predictions of the non-scale endogenous growth models for OECD and non-OECD countries.

III. Description of the Data

The data cover patent applications, full time equivalent (FTE) researchers devoted to R&D sectors and other macroeconomic data. Patent data are obtained from the NBER patent citations database developed by Hall, Jaffe and Trajtenberg (2001). They include all utility patent applications in manufacturing sectors made in the U.S. Patent and Trademark Office by the inventors who reside in different countries. Utility patents are classified according to five main categories: chemicals, computers and

[5] The DT model shown in equation (3) has been criticised on the grounds that it is not consistent with the micro foundations of R/GH/AH models, which implies that new ideas are discovered by individuals and therefore they depend inherently on the number of people. However, several authors including Young (1998) and Aghion and Howitt (1998), developed micro foundations for equations similar to (3). They point out that, at the sector level, innovation rate still depends on the number of human capital, like R/GH/AH, but at the macro level, the research efforts need to be distributed over different products whose demand increases with population.

communication, drugs and medical, electrical and electronics and others.[6] All countries that have patent applications for more than nine consecutive years are included in the analysis. The data on FTE researchers employed in the R&D sectors are obtained from the OECD Main Statistics and Technology Indicators (MSTI) 2003 database.

The remaining macroeconomic variables are from the following sources: GDP and gross fixed investment in 1995 $U.S. and secondary school enrolment (WDI, 2003); the U.S. exports and imports to and from the partner countries (IMF Direction of Trade Database (IMFDOT));[7] imports and exports in goods and services and GDP in current $U.S. (WEO, 2003); and manufacturing imports in the R&D intensive sectors (OECD-MSTI, 2003). The openness variable is constructed by adding up the absolute values of exports and imports in current $U.S. and dividing the total by GDP in current $U.S. The gross ratio of secondary school enrolment is measured as the ratio of total secondary school enrolment, regardless of age, to the population of the age group that officially corresponds to the level of secondary school education. Secondary school

[6] The category "others" include: agriculture-husbandry-food, amusement devices, apparel and textiles, earth working and wells, furniture and house fixtures, heating, pipes and joints, receptacles and miscellaneous.

[7] The U.S. trade share of GDP for each country is calculated by adding up the absolute value of the United States' total exports and imports to and from each partner country and dividing this total by each country's GDP.

data are interpolated by equally distributing the total change across the years for which data are not available.[8]

We use patent data from the U.S. Patent Office to measure innovation, because they provide standardised data for all countries, as all inventors are subject to the same rules and regulations. Furthermore, the U.S. has the largest and the most active market in the world, leading to a high competition among the inventors of different countries to patent in the U.S. Thus, the U.S. patents should provide a good proxy for the rate of technological innovation of countries. However, there are also some potential drawbacks of using patent data from the U.S. to measure innovation. In particular, the geographical distance of the countries to the U.S. and the degree of their economic alliance with the U.S. might have an effect on the number of patent applications made to the U.S. Patent Office. These shortcomings have been taken into account in our econometric modelling.

In addition, following Jaffe and Palmer (1997), we employ successful patent applications instead of granted patents to measure innovation, as the lag-time between application and grant can differ considerably across patents. Moreover, as Jaffe and Palmer (1997) point out, a potentially valuable invention is created at the time of

[8] For example, if the observations in 1980 and 1982 are equal to 100 and 127 respectively, then the observation for 1981 is calculated as (100+((127-100)/3)=109, and the observation for 1982 is calculated as (109+(127-109)/2)=118. This method has the advantage of smoothing out the series so that interpolation will not have a major effect on the results. The results are not sensitive to different types of interpolations, i.e. simple averaging instead of the above method, yields similar results.

patent application rather than the time of the grant year. Furthermore, we use patent flows instead of patent stock to measure innovation, following Kortum (1993). The main drawbacks of using patent data to measure innovation include the variation in the intrinsic value of patents and the inability of patents to capture the whole range of innovations given that not all inventions are patented nor do all patents become successful innovations. However, as Comanor and Scherer (1969) and Griliches (1990, 1994) document in detail, in spite of these shortcomings, patent data still provide significant information on innovation.

Diagnostic tests of the data for unit root, heteroskedasticity and first order autocorrelation show that the series do not have unit root and heteroskedasticity in the majority of the countries, though they exhibit first order autocorrelation.[9] Throughout the analysis, the first order autocorrelation problem has been taken into account by using the first difference series. To determine the cross-country patterns of the main variables of the endogenous growth theories before the estimation of the model, we rank the OECD and non-OECD countries by their aggregate and per capita levels of GDP, patents and full time equivalent researchers. The rankings for per capita levels of these variables are reported in Tables 1 and 2. As these tables show, both in the OECD and non-OECD countries, on average, countries with higher (lower) per capita output also tend to have higher (lower) per capita patents and the share of researchers in

[9] See appendix II, Tables 1A through 4A for the results of the diagnostic tests. The panel data unit root test used in this paper is proposed by Levin, Lin and Chu (2002).

population, indicating a positive correlation between these variables, as suggested by non-scale endogenous growth theories. To determine the correlations between the aggregate levels of output, patents and researchers, we also reported the rankings for these series in Tables 3 and 4. Similar to the figures reported in the preceding tables, the number of patents and the full time equivalent researchers appear to be positively correlated with the GDP levels of countries.

Motivated by the results reported in Tables 1 through 4, we conducted the empirical analysis separately for the high and low income, and large and small market OECD and non-OECD countries.[10] In particular, as the figures in Tables 1 to 4 reveal, countries at the high and low ends of the rankings of aggregate and per capita GDP tend to have, on average, the corresponding levels of aggregate and per capita levels of patents and researchers, suggesting that the countries are not homogenous in terms of the variables of the model.[11] High and low income samples have been constructed by dropping the five median (one median) countries in the rankings of the per capita GDP of OECD (non-OECD) countries reported in the first columns of Tables 1 and 2, and then referring to the countries above (below) the median as high (low) income sample.[12] The large and small market samples have been constructed in a similar manner using the rankings for the aggregate GDP reported in Tables 3 and 4.

[10] Market size is measured by the level of aggregate GDP.

[11] Our presumption that the regression analysis for separate samples yields more robust results than the regression analysis for whole sample is also confirmed by the chow test.

[12] We dropped only one median country from the rankings of the non-OECD country groups when constructing the samples as the non-OECD sample includes fewer countries.

IV. EMPIRICAL ANALYSIS

The estimations of the innovation and production functions have been carried out using the fixed effects and difference GMM analyses. The fixed effects analysis controls for the country specific factors, thus it yields consistent estimators provided that the regressors are exogenous, i.e. they are not correlated with the error term. However, given that the growth regressions are likely to have omitted variable problem, the assumption that the regressors are not correlated with the error term might not hold in the estimation of the production function. To take into account the endogeneity problem to some extent we also employ difference generalized methods of moments (GMM) dynamic panel data estimation proposed by Arellano and Bond (1991), which yields consistent estimators in the presence of regressors that are not exogenous. The difference GMM simply estimates the first difference series by instrumenting them with their appropriate lagged levels. However, as has been pointed out by Blundell, Bond, and Windmeijer (2000), when the series are persistent and the length of the time series data is short, the instrument matrix loses its explanatory power, causing the difference GMM to yield downward biased estimators and large standard errors.

The system GMM analysis proposed by Blundell and Bond (1998) substantially improves upon the difference GMM when the sample size is small and the series are persistent. However, because the system GMM uses a very large instrument matrix, the number of the cross sectional units needs to be sufficiently high for the results to be consistent and efficient, Alvarez and Arellano (2003).[13] Because we have only 41 countries in our data, it was not possible to obtain reliable results with the system GMM estimation. Therefore, we used fixed effects and difference GMM estimations. As mentioned above, in the presence of endogeneity, the fixed effects estimators could be upward biased while the difference GMM yields consistent estimators. However, the estimators of the difference GMM could be downward biased when the series are persistent and the sample size is small. Thus, using these two techniques allows us to check the reliability of our findings and to judge on the pertinence of these two methods. Although our results are not sensitive to the outliers, we still removed them using a standard procedure embodied in STATA.[14] All regressions include the year dummies to control for time specific factors.

Estimation of the Innovation Function

The regression model for the innovation function is constructed by taking the natural log of equation (3) in section II, and including the control variables and the time fixed effects in the model:

[13] Alvarez and Arellano (2003) show that the number of instruments should be lower than the number of cross sectional units for the results of the system GMM estimations to be robust. Otherwise, the system GMM estimators are biased towards those of the OLS.

[14] This procedure, referred to as "hadimvo" in STATA, is developed by Hadi (1992, 1994). The results are not sensitive to the outliers.

$$Log(\dot{A}) = \phi\, Log(A) + \psi\, Log(H_A / L) + \beta\, Log(Z) + \mu + \varepsilon\ , \qquad (4)$$

where $\dot{A}$, A and H_A/L are technological innovation, knowledge stock and the ratio of human capital engaged in R&D to total labour force, respectively. Z is a matrix of control variables; μ is time fixed effects and ε is regression residuals. We measure $\dot{A}$ by patent flows as suggested by Kortum (1993), and H_A/L by the fraction of the full time equivalent researchers devoted to R&D in labour force. The effect of knowledge stock, A, on patent flows has been taken into account by including the lagged patent flows in the analysis. Here it is assumed that the patent flows not only contribute to innovation but also create a knowledge pool for future inventions.

The control variables include the gross ratio of the secondary school enrolment to the population of the secondary school age group, the U.S. trade share of GDP, and an interacted term of manufacturing imports and full time equivalent researchers. The secondary school enrolment rate is a proxy for the overall human capital capacity of a country; the U.S. trade share of GDP measures the technology spillovers from the U.S. and controls for the effect of countries' economic alliance with the U.S on their patent applications to the U.S. Patent Office; and the interacted term of manufacturing imports and full time equivalent researchers engaged in R&D capture the technology spillovers across countries. A positive sign on the coefficient of the interacted term indicates that the higher the imports of the manufacturing goods of a country are, the higher the effect will be of an increase in the number of researchers on innovation.

The results of the fixed effects analysis are reported in Table 6. As observed from the table, the first lag of patent flows is positive in the majority of the samples, while the share of researchers in labour significant only in the full and large market OECD samples.[15] The effect of a 1% increase in the fraction of researchers in labour on patent flows is 0.23% in the full and 0.15% in the large market OECD sample. The remaining variables of the model are not significant in the majority of the samples except that knowledge spillovers and the U.S. trade share of GDP are significant in the large market OECD sample only. In particular, a 1% increase in knowledge spillovers and the U.S. trade share of GDP is associated with a 0.08% and 0.09% increase in patent flows, respectively. To check the robustness of the fixed effects results, we also report the findings of the difference GMM in Table 7. As the table shows, the main difference between the fixed effects and difference GMM results is that in the latter the coefficient of the share of researchers in labour is not significant in the full sample, while it is significant in the large market and high income OECD countries. However, because the p value of the sargan test for the high income sample is very low, the regression model of this sample does not yield robust results. Thus only the large market OECD sample remains to have positive returns to their researchers in terms of innovation. In this sample, a 1% increase in the fraction of researchers in labour leads to a 0.20% increase in patent flows, providing support for non-scale endogenous growth models.

[15] See Table 5 for the list of the countries in each sample.

As regards to the other variables of the model, the first lag of patent flows and knowledge spillovers are significant in the large market OECD sample only, implying that only these countries are able to utilize the intertemporal and cross-country knowledge spillovers to increase innovation. In addition, the U.S. trade share of GDP is not significant in any of the samples, while the secondary school enrolment is significant only in the high income OECD sample.[16] The fact that the U.S. trade share of GDP is not significant in any of the samples implies that there are not significant knowledge spillovers from the U.S. to other OECD countries. It also suggests that a closer economic alliance with the U.S. does not have a significant effect on patent applications made in the U.S. Furthermore, the secondary school enrolment does not seem to be a satisfactory proxy for the overall human capital capacity of countries, given that it is not significant in the majority of the samples.

In summary, we can conclude that the large market OECD countries that include the G7 verify the prediction of the non-scale endogenous growth models that an increase in the fraction of researchers in labour promotes innovation. They also effectively utilize the intertemporal and cross-country knowledge spillovers to increase their innovation. It is not surprising that only these countries are able to have significant returns to their researchers and absorb knowledge spillovers better, given that they allocate larger resources to R&D and innovative activities than other OECD countries.

[16] Although the coefficient of the lagged patent flows is also positive in the full OECD sample, the regression model for this sample does not have an explanatory power, as indicated by the low p value of the sargan test.

Estimation of the Production Function

The regression model of the production function is derived from equation (1) in section II. In particular, after scaling output and investment in equation (1) by labour, and human capital by population, we include the openness to trade variable in the model and take the natural log of the equation.[17] The resulting regression equation is as follows:

$$y = Log\ A + \alpha\ Log(x) + \beta\ Log(h) + \gamma\ Log(z) + \mu + \varepsilon\,, \qquad (5)$$

where y, A, x, h , z and μ are per labour output, technological innovation measured by patent flows, per labour physical investment, the secondary school enrolment rate, openness to trade and time fixed effects, respectively. The results of the fixed effects and GMM estimations for OECD and non-OECD samples are reported in Tables 8 through 12.[18]

As observed from Table 8 that reports the fixed effects results for OECD samples, per labour investment has a positive coefficient in all samples, with a value ranging from 0.22 in the high income and 0.52 in the large market OECD countries. However, the

[17] The production function has been scaled by the labour series, instead of population, to eliminate the multicollinearity problem arising from a high correlation between investment and labour.

[18] See Table 5 for the list of the countries in each sample.

coefficient of patent flows is significant only in the full, high income and low-income OECD countries. Specifically, a 1% increase in patent flows increases per labour GDP by 0.05% in the full, 0.07% in the high income and 0.04% in the low income OECD countries. As expected, the degree of openness to trade is positively associated with per labour GDP in all samples, providing support for the view that trade liberalization has a positive impact on per capita income. Though the t value of the secondary school enrolment rate is high in all samples, it has a significant impact on per labour GDP only in the full, high and low income OECD countries. More specifically, a 1% increase in the secondary school enrolment rate leads to a 0.19% increase in per labour GDP in the high income OECD, while it leads to a 0.10% increase in the full and low income OECD countries.

The findings of difference GMM reported in Table 9 are very similar to those of the fixed effects. The only two exceptions are that in the GMM analysis the patent flows remain significant only in the high income OECD sample and the secondary school enrolment becomes insignificant in all samples.[19] The coefficient of per labour investment is still positive in all OECD samples with a value ranging from 0.13 in the small market to 0.30 in the large market OECD countries. Returns to patent flows in terms of per labour GDP is marginally significant in the high income OECD countries only and the magnitude of these returns are lower (0.02) than those in the fixed effects

[19] The results of the full sample are disregarded, as the regression model for this sample does not pass the sargan test.

analysis (0.07). In addition, the degree of openness to trade seems to be still positively related to per capita income in the majority of the countries.

For a further robustness check, we also estimated per labour GDP in terms of the share of researchers in labour instead of patent flows. As seen from Table 10, only the high income OECD countries enjoy higher per labour GDP as a result of higher fraction of researchers in labour, providing strong support for the results obtained in the preceding section. Overall, combining the information obtained from the estimation of the production function with different techniques and different variables, we can conclude that only the high income OECD countries seem to verify the prediction of the endogenous growth theories that an increase in innovation promotes per capita GDP. The findings also suggest that the majority of the OECD samples enjoy higher per labour GDP as a result of higher degree of trade liberalization, and per labour investment is an important determinant of per labour GDP in all samples.

The estimation results of the production function for the non-OECD countries are reported in Tables 11and 12. The fixed effects results (Table 11) seem to confirm our expectation that the variables of the model are positively associated with per labour GDP in the majority of the samples, with an exception that the secondary school enrolment is not significant in most of the samples and negative in the small market sample. As expected, returns to per labour GDP are positive in all samples and range between 0.22% in the small market and 0.58% in the large market non-OECD samples. The coefficient of patent flows is significant in the full, large market and high income non-OECD samples only, with the respective values of 0.02. 0.03 and 0.13. In addition, the relationship between trade liberalization and per labour GDP is positive in the full, high income and low income non-OECD countries, while it is negative in the small market, and insignificant in the large market non-OECD countries (though it has a high t value).

The difference GMM analysis appears to improve upon the fixed effects results. As observed in Table 12, per labour investment still has a positive impact on per labour GDP in all samples. Similar to the fixed effects results, the highest impact of per labour investment on per labour GDP is in the large market (0.35), while its lowest impact is in the small market non-OECD countries (0.11). As expected, the magnitudes of these impacts are lower in the GMM than in the fixed effects analysis. Interestingly, all samples of the non-OECD countries, except for the low income countries, have positive returns to their patent flows. Specifically, a 1% increase in patent flows leads to a 0.08% increase in the high income and around 0.02% increase in the large and small market non-OECD samples.[20] Moreover, a higher degree of openness to trade is positively associated with per labour GDP only in the high and low income non-OECD countries, while the effect of an increase in secondary school enrolment rate is positive only in the large market and high income non-OECD countries.

[20] The results for the full sample are disregarded here as the regression model for this sample does not have an explanatory power as indicated by the low p value of the sargan test.

In summary, putting together the findings obtained from the fixed effects and difference GMM estimations of the production function for the OECD and non-OECD samples, we can conclude that, both in the OECD and non-OECD countries, the high income countries seem to benefit most from investing in innovation. In particular, according to the fixed effects and GMM results, returns to the patent flows of the high income OECD countries are between 0.02% and 0.07%, while the returns to those of the high income non-OECD countries are between 0.08% and 0.13%. Moreover, unlike the OECD samples in which only the high income countries have positive returns to their patent flows in terms of per labour GDP, in the non-OECD countries the large and small market samples also have positive returns, though their magnitudes are very modest (between 0.02% and 0.03%).

The fact that the high income countries have the highest returns to their innovation with respect to per labour GDP implies that, on average, the economic value of patents might be higher in high income countries compared to others. It also suggests that the way in which high income countries utilize new information and innovation in the production process might be different from other countries. Considering that the innovation activities are resource intensive and upgrading production process for new technology is an expensive process, it is not surprising that the high income countries have the largest returns to their innovation in terms of per labour GDP. The remaining variables of the production function also seem to confirm the theoretical expectations. In particular, the contribution of per labour investment to per labour GDP is very significant in all samples, and the higher degree of openness to trade seems to be associated with a higher per labour GDP in the majority of the samples. However, the coefficient of the secondary school enrolment appears to be insignificant in most of the samples, reflecting the fact that these series might not be a good proxy for the human capital capacity of countries.

V. CONCLUSION

The objective of this paper was to analyze the main implications of the non-scale endogenous growth theories using panel data from both developed and developing countries. In particular, we examined the following two implications of these models: an increase in the fraction of researchers in total labour force leads to an increase in innovation, and an increase in innovation raises per capita output. Our findings show that an increase in the share of researchers in labour has a positive effect on innovation only in the large market OECD countries that include the G7. The fact that this result is robust to different regression techniques indicates that the market size, holding other things constant, is an important determinant of the effectiveness of R&D sectors in promoting innovation. However, we should also note that the large market OECD countries include the most industrialized countries that have high per capita incomes and established institutions, which are fundamental in promoting R&D sectors and achieving high level of technological innovation. Furthermore, historically, the large market OECD countries, the G7 in particular, have highly competitive R&D sectors and have been the world leaders in technological innovation.

The findings also suggest that the developing countries benefit more from innovation than developed countries in promoting per labour GDP. In particular, according to the results of the analyses, innovation raises per labour GDP in the high income OECD countries only, while raising it in all non-OECD countries, except for the low income countries. In addition, the high income non-OECD countries have higher returns to their innovation in terms of per labour GDP than the high income OECD countries. As expected, a higher degree of openness to trade is associated with higher per labour GDP in the majority of the OECD and non-OECD countries. However, the effect of secondary school enrolment rate on innovation and per labour GDP seems to be insignificant in most of the samples.

Overall, the results of our empirical analysis lend strong support to non-scale endogenous growth models. However, a main limitation of this study is that the patent applications used in the analysis include only the applications made in the U.S. Patent Office. Though the U.S. patent data have many advantages over the patent data that can be obtained from each country's patent offices, such as the standardization and the reliability of data, they might underestimate the propensity to patent, especially in the non-OECD countries. This study, therefore, can be extended to include case studies for developing countries that utilise sector level patent and R&D data, given that the aggregate data on patents are not reliable in these countries and the majority of these countries do not have aggregate R&D data. We should also not that the patents are only a limited proxy for technological innovation, as not all inventions are patented and not all patented inventions become innovation. However, in spite of these limitations, our results are able to provide consistent information on the relationships between R&D, innovation and per labour GDP. The main contribution of this study to the existing literature is that it provides a comparative analysis of the non-scale endogenous growth theories across developed and developing countries, as well as across samples with different income levels and market sizes.

Table 1. Rankings of OECD Countries by Per Capita GDP, Patents and Researchers, 1981-97

Rank	Country	Per Capita GDP	Country	Per Capita Patents	Country	Per Capita Researchers
1	Switzerland	42840	Switzerland	175.90	Japan	4436
2	Japan	36981	Japan	156.40	Sweden	3015
3	Denmark	31418	Sweden	94.50	Iceland	2892
4	Norway	29155	Germany	89.20	Norway	2885
5	Germany	27359	Canada	67.20	Finland	2813
6	Austria	26310	Finland	63.40	Switzerland	2651
7	Sweden	25733	Netherlands	57.50	Australia	2508
8	Iceland	25449	France	48.80	Canada	2371
9	France	24731	United Kingdom	44.60	Germany	2353
10	Belgium	24545	Austria	43.60	United Kingdom	2329
11	Finland	24379	Denmark	41.90	Korea	2215
12	Netherlands	24042	Belgium	35.80	Denmark	2203
13	Canada	18528	Norway	28.40	France	2155
14	Australia	18491	Australia	25.60	Netherlands	1871
15	Italy	17284	Italy	19.90	Belgium	1806
16	United Kingdom	17245	Korea	18.40	New Zealand	1683
17	New Zealand	15548	New Zealand	16.00	Austria	1336
18	Ireland	14528	Iceland	14.50	Poland	1334
19	Spain	13081	Ireland	14.40	Italy	1224
20	Greece	10787	Hungary	7.57	Hungary	1215
21	Portugal	9225	Spain	3.44	Ireland	1174
22	Korea	7625	Greece	1.01	Spain	875
23	Hungary	4553	Portugal	0.50	Greece	778
24	Mexico	3236	Mexico	0.50	Portugal	726
25	Poland	2734	Poland	0.32	Turkey	241
26	Turkey	2466	Turkey	0.05	Mexico	201

Sources: GDP (WDI 2003), patents (NBER Patent Citation Database), researchers (OECD).
Note: Per capita GDP is in 1995 $U.S. Per capita patents and researchers are per million people.

Table 2. Rankings of Non-OECD Countries by Per Capita GDP and Patents, 1981–97

Rank	Country	Per Capita GDP	Country	Per Capita Patents
1	Hong Kong	18242	Israel	68.60
2	Singapore	17557	Singapore	11.70
3	Israel	13746	Hong Kong	10.00
4	Argentina	6958	South Africa	2.89
5	Brazil	4158	Bulgaria	1.55
6	South Africa	4153	Venezuela	1.12
7	Venezuela	3535	Argentina	0.70
8	Malaysia	3240	Malaysia	0.43
9	Colombia	2093	Brazil	0.31
10	Romania	1693	Colombia	0.14
11	Bulgaria	1584	Romania	0.10
12	Philippines	1082	Philippines	0.07
13	Indonesia	776	China	0.04
14	China	374	India	0.03
15	India	311	Indonesia	0.02

Sources: GDP (WDI 2003), patents (NBER Patent Citation Database). Non-OECD countries do not have R&D data. Per capita GDP is in 1995 $U.S. Per capita patents and researchers are per million people.

Table 3. Rankings of OECD Countries by Aggregate GDP, Patents and Researchers, 1981–97

Rank	Country	GDP	Country	Patent	Country	Researchers
1	Japan	4546000	Japan	19286	Japan	545358
2	Germany	2178000	Germany	7098	Germany	187722
3	France	1395000	France	2752	United Kingdom	133591
4	United Kingdom	990500	United Kingdom	2561	France	121763
5	Italy	982500	Canada	1866	Korea	100850
6	Canada	509300	Switzerland	1177	Italy	69541
7	Spain	507400	Italy	1132	Canada	65678
8	Netherlands	359100	Netherlands	858	Poland	51484
9	Korea	328700	Korea	823	Australia	42654
10	Australia	311500	Sweden	809	Spain	34024
11	Switzerland	287300	Australia	433	Netherlands	27986
12	Mexico	264400	Belgium	358	Sweden	25871
13	Belgium	245100	Austria	339	Mexico	18382
14	Sweden	220100	Finland	318	Switzerland	18121
15	Austria	204500	Denmark	217	Belgium	18051
16	Denmark	162200	Spain	134	Turkey	14583
17	Turkey	136900	Norway	121	Finland	14128
18	Norway	123800	Hungary	79	Hungary	12495
19	Finland	121500	New Zealand	55	Norway	12284
20	Greece	109400	Ireland	51	Denmark	11397
21	Poland	105200	Mexico	41	Austria	10439
22	Portugal	91590	Poland	12	Greece	8063
23	New Zealand	53270	Greece	10	Portugal	7209
24	Ireland	51630	Portugal	5	New Zealand	6030
25	Hungary	47490	Iceland	4	Ireland	4177
26	Iceland	6432	Turkey	3	Iceland	751

Table 4. Rankings of Non-OECD Countries by Aggregate and Per Capita GDP, 1981–97[21]

Rank	Country	GDP	Country	Patent
1	Brazil	604700	Israel	339
2	China	428600	South Africa	99
3	India	263600	Hong Kong	59
4	Argentina	223900	Brazil	46
5	South Africa	142000	China	40
6	Indonesia	138700	Singapore	40
7	Hong Kong	105600	India	30
8	Colombia	72670	Argentina	23
9	Venezuela	67280	Venezuela	22
10	Israel	66040	Bulgaria	14
11	Philippines	64710	Malaysia	8
12	Malaysia	59120	Colombia	5
13	Singapore	55160	Philippines	4
14	Romania	38560	Indonesia	3
15	Bulgaria	13900	Romania	2

Sources: GDP (WDI 2003), Patents (NBER Patent Citation Database), Researchers (OECD-MSTI 2003), R&D data were not available for non-OECD countries. GDP is in 1995 millions $U.S., per capita patents are per million people.

[21] Korea, Mexico, Poland, Turkey and Hungary have data on researcher only after 1990, which might have contributed to their higher rankings in the number of researchers. The numbers of observations on researchers for these countries are: Korea 3, Poland 4, Hungary 8, Mexico 5 and Turkey 8. All the remaining countries have data on the number of researchers for 17 years, except for Greece, which has 9-year data.

Table 5. List of the Countries in Each Sample

Full Sample		High Income	Low Income	Large Market	Small Market
OECD	Poland	OECD	OECD	OECD	OECD
G7	Portugal	Austria	Greece	Australia	Denmark
Canada	Spain	Belgium	Hungary	Canada	Finland
France	Sweden	Denmark	Ireland	France	Greece
Germany	Switzerland	Finland	Korea	Germany	Hungary
Italy	Turkey	France	Mexico	Italy	Iceland
Japan	Non-OECD	Germany	New Zealand	Japan	Ireland
UK	Argentina	Iceland	Poland	Netherlands	New Zealand
Non-G7	Brazil	Japan	Portugal	Spain	Norway
Australia	Bulgaria	Norway	Spain	UK	Poland
Austria	China	Sweden	Turkey		Portugal
Belgium	Colombia	Switzerland			Turkey
Denmark	Hong Kong				
Finland	India				
Greece	Indonesia	Non-OECD	Non-OECD	Non-OECD	Non-OECD
Hungary	Israel	Hong Kong	Colombia	Brazil	Israel
Iceland	Malaysia	Singapore	Romania	China	Philippines
Ireland	Philippines	Israel	Bulgaria	India	Malaysia
Korea	Romania	Argentina	Philippines	Argentina	Singapore
Mexico	Singapore	Brazil	Indonesia	South Africa	Romania
Netherlands	South Africa	South Africa	China	Indonesia	Bulgaria
New Zealand	Venezuela	Venezuela	India	Hong Kong	Venezuela
Norway					

Note: Countries with aggregate GDP above (below) the median GDP are referred to as large (small) market OECD, and countries with per capita income above (below) the median per capita income are referred to as high (low) income OECD countries (median countries are dropped).
Hungary, Korea, Mexico, Turkey and Poland are not included in the regression analysis of patent flows as these countries have less than 9 data points. The patent regression includes 21 OECD countries, while the GDP regression includes all 41 countries listed above. Israel is not included in the small market non-OECD sample as it is an outlier, i.e. it has the highest per capita income and patents.

Table 6. Fixed Effects Regression Analysis of Per Labour Patent Flows, OECD Samples, 1981-1997

	Full OECD	Large Market	Small Market	High Income	Low Income
L1. Patent flows	0.259	0.709	0.154	0.279	0.035
	(4.40)***	(11.30)***	(1.50)	(3.29)***	(0.24)
Researchers/labour	0.250	0.153	-0.662	0.241	-0.466
	(1.99)**	(2.07)**	(1.53)	(0.95)	(0.78)
U.S. trade/GDP	0.103	0.093	0.129	0.008	-0.003
	(1.06)	(1.95)*	(0.62)	(0.06)	(0.01)
Knowledge spillovers	0.073	0.077	-0.064	0.238	-0.353
	(0.68)	(1.67)*	(0.26)	(1.51)	(1.19)
Secondary school enrolment	-0.120	-0.110	0.468	0.043	0.131
	(0.61)	(1.51)	(0.74)	(0.13)	(0.20)
Constant	3.148	1.026	2.535	0.583	5.780
	(2.51)**	(1.46)	(0.84)	(0.26)	(1.63)
Observations	319	142	121	167	74
Number of ccode1	22	9	9	11	6
R-squared	0.53	0.94	0.51	0.53	0.68

Absolute value of t statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
Note: All variables are in natural logs, and all regressions include time fixed effects. L1 stands for first lag. Knowledge sipllovers are measured as an interacted term of researchers and manufacturing imports.

Table 7. One Step Difference GMM Regression Analysis of Per Labour Patent Flows, OECD Samples, 1981-1997

	Full OECD	Large Market	Small Market	High Income	Low Income
LD. Patent Flows	0.235	0.511	0.127	-0.078	0.114
	(4.31)***	(5.72)***	(1.40)	(1.30)	(1.04)
D. Researchers/labour	0.007	0.202	-0.610	0.274	-0.229
	(0.04)	(2.08)**	(1.42)	(2.33)**	(0.47)
D. Knowledge spilllover	0.061	0.080	-0.054	0.022	-0.328
	(0.53)	(1.79)*	(0.27)	(0.31)	(1.49)
D.U.S. trade/GDP	0.049	0.007	0.150	0.009	0.182
	(0.41)	(0.12)	(0.78)	(0.11)	(0.89)
D. Secondary school enrolment	0.006	-0.028	0.040	0.484	-0.141
	(0.03)	(0.42)	(0.08)	(3.77)***	(0.28)
Constant	-0.043	-0.008	-0.038	0.037	0.219
	(0.62)	(1.28)	(0.17)	(0.75)	(3.27)***
Sargan test, p value[a]	0.00	0.96	0.99	0.02	1.00
AR(2) test, p value[b]	0.36	0.19	0.19	0.20	0.53
Observations	282	132	99	113	64
Number of ccode1	22	9	9	11	6

Absolute value of z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
Note: All variables are in natural logs and all regressions include time fixed effects. D stands for first difference, LD stands for lagged dependent variable. Knowledge sipllovers are measured as an interacted term of researchers and manufacturing Imports.
a/ H_0: regressors are not correlated with the residuals.
b/ H_0: errors in first difference regression exhibit no second order serial correlation.

Table 8. Fixed Effects Regression Analysis of Per Labour GDP, OECD Samples, 1981-1997

	Full OECD Sample	Large Market	Small Market	High Income	Low Income
Per labour investment	0.318	0.528	0.231	0.222	0.411
	(15.37)***	(9.29)***	(6.64)***	(5.62)***	(11.77)***
Patent flows	0.050	0.021	0.010	0.074	0.038
	(7.14)***	(0.65)	(0.90)	(4.47)***	(3.40)***
Openness to trade	0.080	0.064	0.205	0.104	0.102
	(3.30)***	(1.60)	(5.56)***	(1.84)*	(2.84)***
Secondary school enrolment	0.111	0.070	0.070	0.193	0.099
	(3.79)***	(1.56)	(1.38)	(3.20)***	(1.80)*
Constant	6.509	5.153	6.966	7.051	5.400
	(29.74)***	(10.42)***	(21.69)***	(14.01)***	(16.00)***
Observations	418	153	163	187	146
Number of ifs	26	9	11	11	10
R-squared	0.81	0.82	0.82	0.72	0.86

Absolute value of t statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
Note: All variables are in natural logs and all regressions include time fixed effects. Openness to trade is measured as the ratio of total trade to GDP.

Table 9. One Step Difference GMM Regression Analysis of Per Labour GDP, OECD Samples, 1981-1997

	Full OECD Sample	Large Market	Small Market	High Income	Low Income
LD. Per labour GDP	0.615	0.625	0.632	0.786	0.623
	(15.45)***	(7.80)***	(7.61)***	(10.31)***	(7.42)***
D. Per labour investment	0.222	0.298	0.135	0.136	0.184
	(12.50)***	(6.64)***	(4.98)***	(4.42)***	(6.27)***
D. Patent flows	0.009	-0.016	-0.003	0.015	-0.004
	(2.08)**	(0.57)	(0.48)	(1.63)*	(0.54)
D. Openness to trade	0.023	0.067	0.074	0.152	0.018
	(1.41)	(2.51)**	(2.91)***	(3.98)***	(0.79)
D. Secondary school enrolment	-0.066	0.000	-0.036	0.016	0.019
	(2.70)***	(0.02)	(0.96)	(0.46)	(0.57)
Constant	0.014	-0.001	0.012	0.001	0.007
	(4.48)***	(0.58)	(4.34)***	(1.35)	(2.32)**
Sargan test, p value[a]	0.00	0.18	0.42	0.08	0.41
AR(2) test, p value[b]	0.57	0.69	0.62	0.96	0.88
Observations	366	126	130	154	116
Number of ifs	26	9	11	11	10

Absolute value of z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
Note: All variables are in natural logs and all regressions include time fixed effects. D stands for first difference and LD stands for lagged dependent. Openness to trade is measured as the ratio of total trade to GDP.
a/ H_0: regressors are not correlated with the residuals.
b/ H_0: errors in first difference regression exhibit no second order serial correlation.

Table 10. One Step Difference GMM Regression Analysis of Per Labour GDP, OECD Samples, 1981-1997

	Full OECD Sample	Large Market	Small Market	High Income	Low Income
LD. Per labour GDP	0.673	0.641	0.568	0.697	0.733
	(16.71)***	(13.31)***	(9.65)***	(9.02)***	(11.42)***
D. Per labour investment	0.172	0.286	0.135	0.162	0.121
	(8.73)***	(6.83)***	(5.62)***	(5.33)***	(3.57)***
D. Researchers/labour	0.026	-0.065	0.032	0.058	-0.016
	(1.46)	(1.89)*	(1.33)	(1.98)**	(0.39)
D. Openness to trade	0.038	0.094	0.094	0.159	0.014
	(1.94)*	(3.38)***	(4.09)***	(4.18)***	(0.43)
D. Secondary school enrolment	-0.041	0.006	-0.025	-0.007	-0.008
	(1.69)*	(0.26)	(0.75)	(0.19)	(0.19)
Constant	0.004	0.002	-0.020	0.001	0.010
	(0.59)	(1.43)	(1.52)	(0.88)	(2.37)**
Sargan test, p value[a]	0.00	0.17	0.11	0.14	0.97
AR(2) test, p value[b]	0.60	0.72	0.38	0.90	0.25
Observations	311	133	120	147	82
Number of ifs	26	9	11	11	10

Absolute value of z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%
Note: All variables are in natural logs and all regressions include time fixed effects. D stands for first difference and LD stands for lagged dependent. Openness to trade is measured as the ratio of total trade to GDP.
a/ H_0: regressors are not correlated with the residuals.
b/ H_0: errors in first difference regression exhibit no second order serial correlation.

Table 11. Fixed Effects Regression Analysis of Per Labour GDP, Non-OECD Samples, 1981-1997

	Full Non-OECD	Large Market	Small Market	High Income	Low Income
Per labour investment	0.459	0.584	0.226	0.458	0.498
	(17.33)***	(19.24)***	(4.02)***	(11.03)***	(8.10)***
Patent flows	0.019	0.032	0.022	0.135	-0.000
	(2.20)**	(3.03)***	(1.19)	(7.38)***	(0.03)
Openness to trade	0.109	0.043	-0.127	0.105	0.110
	(5.37)***	(1.55)	(2.55)**	(3.18)***	(2.80)***
Secondary school enrolment	0.023	0.272	-0.318	0.082	0.079
	(0.42)	(4.72)***	(1.94)*	(0.96)	(0.77)
Constant	4.867	3.190	8.739	4.822	3.909
	(14.74)***	(11.28)***	(9.43)***	(7.82)***	(7.24)***
Observations	217	103	65	109	95
Number of ifs	15	7	5	7	7
R-squared	0.85	0.96	0.89	0.86	0.90

Absolute value of t statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
Note: All variables are in natural logs and all regressions include time fixed effects. Openness to trade is measured as the ratio of total trade to GDP.

Table 12. One Step Difference GMM Regression Analysis of Per Labour GDP, Non-OECD Samples, 1981-1997

	Full Non-OECD	Large Market	Small Market	High Income	Low Income
LD. Per labour GDP	0.669	0.442	0.679	0.566	0.696
	(20.45)***	(8.53)***	(12.96)***	(9.44)***	(19.55)***
D. Per labour investment	0.167	0.345	0.116	0.207	0.209
	(8.31)***	(9.22)***	(5.03)***	(5.48)***	(8.04)***
D. Patent flows	0.012	0.018	0.017	0.078	0.001
	(2.30)**	(2.31)**	(2.22)**	(5.05)***	(0.19)
D. Openness to trade	0.028	-0.000	-0.013	0.057	0.027
	(2.21)**	(0.00)	(0.65)	(2.01)**	(1.84)*
D. Secondary school enrolment	0.064	0.183	-0.094	0.134	-0.025
	(1.83)*	(4.50)***	(1.31)	(2.52)**	(0.66)
Constant	0.032	0.013	0.028	0.027	0.033
	(2.25)**	(2.65)***	(2.18)**	(1.33)	(1.72)*
Sargan test, p value[a]	0.00	0.99	1.00	0.99	0.96
AR(2) test, p value[b]	0.73	0.95	0.69	0.99	0.67
Observations	186	89	54	94	81
Number of ifs	15	7	5	7	7

Absolute value of z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%

Note: All variables are in natural logs and all regressions include time fixed effects. D stands for first difference and LD stands for lagged dependent. Openness to trade is measured as the ratio of total trade to GDP.

a/ H_0: regressors are not correlated with the residuals.

b/ H_0: errors in first difference regression exhibit no second order serial correlation.

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Appendix: Statistical Analysis of Data

Table 1A. Heteroskedasticity and First Order Autocorrelation Test for the Fitted Values of Patents

Durbin-Watson d-statistics[1]				Breusch-Pagan / Cook-Weisberg test for heteroskedasticity[2] Ho: Constant variance, variables: fitted values of patent rate			
Australia	1.30	Italy	2.52	Australia	2.69 (0.10)	Italy	0.09 (0.76)
Austria	2.44	Japan	1.46	Austria	1.54 (0.21)	Japan	5.46 (0.01)
Belgium	2.03	Netherlands	1.22	Belgium	4.26 (0.03)	Netherlands	3.13 (0.07)
Canada	1.31	New Zealand	2.93	Canada	0.04 (0.83)	New Zealand	0.00 (0.98)
Denmark	2.09	Norway	1.99	Denmark	4.10 (0.04)	Norway	1.06 (0.30)
Finland	1.76	Portugal	1.86	Finland	0.05 (0.83)	Portugal	0.83 (0.36)
France	1.60	Spain	3.23	France	0.44 (0.50)	Spain	0.83 (0.36)
Germany	1.22	Sweden	1.46	Germany	0.15 (0.69)	Sweden	7.81 (0.00)
Greece	2.36	Switzerland	1.20	Greece	0.11 (0.73)	Switzerland	0.03 (0.85)
Iceland	1.57	UK	1.39	Iceland	0.47 (0.49)	UK	3.03 (0.08)
Ireland	1.95			Ireland	0.01 (0.92)		

Notes: Figures in parenthesis are p values.
1/ The values of d-statistics below or above 2 indicate the presence of first order autocorrelation.

Table 2A. Heteroskedasticity and First Order Auto Correlation Test for the Fitted Values of Per Labour GDP

Durbin-Watson d-statistic [1]				Breusch-Pagan / Cook-Weisberg test for heteroskedasticity Ho: Constant variance Variables: fitted values of patent rate			
Argentina	1.42	Italy	1.99	Argentina	2.01 (0.15)	Italy	0.05 (0.81)
Australia	1.75	Japan	2.47	Australia	2.09 (0.14)	Japan	0.79 (0.37)
Austria	0.81	Korea	1.51	Austria	1.51 (0.21)	Korea	0.22 (0.64)
Belgium	1.06	Malaysia	2.35	Belgium	3.49 (0.06)	Malaysia	0.17 (0.68)
Brazil	1.72	Mexico	2.22	Brazil	0.45 (0.50)	Mexico	0.07 (0.78)
Bulgaria	1.26	Netherlands	0.84	Bulgaria	0.80 (0.36)	Netherlands	0.00 (0.96)
Canada	1.21	New Zealand	1.97	Canada	7.16 (0.00)	New Zealand	1.36 (0.24)
China	1.43	Norway	1.01	China	0.48 (0.48)	Norway	3.47 (0.06)
Colombia	1.66	Philippines	2.32	Colombia	0.30 (0.58)	Philippines	0.92 (0.33)
Denmark	1.80	Poland	2.88	Denmark	0.02 (0.88)	Poland	0.61 (0.43)
Finland	1.37	Portugal	1.02	Finland	1.40 (0.23)	Portugal	2.15 (0.14)
France	2.23	Romania	2.63	France	0.31 (0.57)	Romania	0.23 (0.63)
Germany	1.20	Singapore	2.82	Germany	0.82 (0.36)	Singapore	0.34 (0.55)
Greece	2.47	South Africa	3.13	Greece	0.00 (0.94)	South Africa	0.51 (0.47)
Hong Kong	1.63	Spain	1.40	Hong Kong	0.06 (0.80)	Spain	1.12 (0.28)
Hungary	2.53	Sweden	1.79	Hungary	1.28 (0.25)	Sweden	0.41 (0.52)
Iceland	1.42	Switzerland	1.92	Iceland	0.11 (0.74)	Switzerland	4.44 (0.03)
India	1.84	Turkey	2.50	India	0.11 (0.73)	Turkey	0.14 (0.71)
Indonesia	2.92	UK	2.14	Indonesia	0.66 (0.41)	UK	0.20 (0.65)
Ireland	2.10	Venezuela	2.05	Ireland	1.70 (0.19)	Venezuela	0.09 (0.76)
Israel	1.74			Israel	0.78 (0.37)		

Figures in parenthesis are p values.
1/ The values of d-statistics below or above 2 indicate the presence of first order autocorrelation.

Table 3A. Levin-Lin-Chu Panel Data Unit Root Test of the Variables in Patent Regression[1]

Variables in patent regression			Variables in GDP and TFP Regression				
OECD sample				OECD Sample		Non-OECD Sample	
Variables	t-star	p value	Variables	t-star	p value	t-star	p value
Patent	-2.96	0.00	PL. GDP	-3.11	-2.14	-2.06	0.02
PL Researchers	-2.95	0.00	PL. Investment	-3.51	-2.31	-2.11	0.02
Sec. school enr.	-1.92	0.03	Patents	-6.55	-4.26	-2.15	0.02
Man. import*researchers	-2.85	0.00	Sec. school enr.	3.54	6.70	-3.36	0.00
U.S. trade/GDP	-4.34	0.00	Openness	-5.64	-2.85	-2.42	0.01
D1.Patent	-14.5	0.00	D1.PL. GDP	-10.0	-7.80	-11.0	0.00
D1.PL researchers	-6.98	0.00	D1.PL investment	-8.50	-6.01	-10.1	0.00
D1.Sec. school enrolment	-8.79	0.00	D1. Patents	-16.8	-14.6	-26.2	0.00
D1.Man. imports* researchers	-8.23	0.00	D1.Sec.school enr.	-2.45	1.71	-7.28	0.00
D1.U.S. trade/GDP	-10.5	0.00	D1.Openness	-12.2	-10.2	-12.8	0.00

1/ t-star statistics is distributed as standard normal under the null hypothesis of nonstationarity.
Note: All variables are in natural log. PL stands fro per labour; D1 stands for first difference series. The statistics for first difference series are reported as the system GMM analysis uses both level and difference series.

Table 4A: Summary Statistics Variables in the Patent Regression

	Full OECD sample (Sample size: 323)				High Income OECD Sample size: 170				Low Income OECD Sample size: 66			
Variable	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
Patents	5.93	2.16	0.00	10.23	6.33	2.20	0.00	10.23	3.48	1.26	1.10	5.34
Researchers/labour	1.39	0.47	-0.29	2.36	1.60	0.35	0.74	2.36	0.79	0.44	-0.29	1.53
Secondary school	4.61	0.17	3.90	5.06	4.64	0.12	4.45	5.06	4.56	0.20	3.90	4.80
US trade/GDP	1.43	0.74	0.09	3.94	1.27	0.51	0.18	2.38	1.29	0.77	0.09	2.58
Knowledge spillovers	5.47	0.59	3.80	6.75	5.70	0.40	5.01	6.75	4.89	0.72	3.80	6.52

Note: All variables are in natural logs. PL stands for per labour. Std stands for standard deviation.

Table 5A. Correlation Coefficients of the Variables in the Patent Regression

	Patents	Researchers/ labour	Secondary School	US trade/GDP	Knowledge Spillovers
Patents	1				
Researchers/labour	0.5832*	1			
Secondary school	0.1498*	0.4836*	1		
US trade/GDP	0.0741	0.1927*	0.0382	1	
Knowledge spillovers	0.2047*	0.6732*	0.5925*	0.3991*	1

Note: All variables are in natural logs. PL stands for per labour. * Significant at 10%
Knowledge spillovers are measured as an interactive term of manufacturing imports and researchers.

Table 6A: Summary Statistics Variables in GDP and TFP Regressions

Full Non OECD Sample (N=217)					High Income non-OECD Sample (N=109)				Low income non-OECD Sample (N=95)			
stats	sd	min	max	mean	sd	min	max	mean	sd	max	mean	min
PL GDP	1.18	5.94	10.87	9.04	0.58	9.08	10.87	9.94	0.88	9.56	7.99	5.94
PL inv	1.20	4.62	9.93	7.54	0.76	7.18	9.93	8.41	0.78	8.07	6.49	4.62
Patents	1.46	0.00	6.48	2.94	1.15	1.39	6.48	3.79	1.26	4.42	2.10	0.00
Sec.school	0.34	3.08	4.62	4.06	0.39	3.08	4.57	4.07	0.29	4.62	4.05	3.45
Openness	0.97	2.58	6.02	3.95	1.14	2.58	6.02	4.17	0.55	4.79	3.54	2.63
Full OECD sample (N=418)					High income OECD Sample (N=187)				Low income OECD Sample (N=146)			
Stats	sd	max	mean	min	sd	max	mean	min	sd	max	mean	min
PL GDP	0.64	11.32	10.52	8.53	0.16	11.32	10.98	10.61	0.62	10.86	9.85	8.53
PL inv	0.66	10.09	8.94	6.74	0.27	10.09	9.41	8.85	0.64	9.24	8.30	6.74
Patents	2.34	10.23	5.41	0.00	2.23	10.23	6.26	0.00	1.60	8.11	3.39	0.00
Sec.school	0.22	5.06	4.55	3.72	0.11	5.06	4.64	4.45	0.27	4.80	4.42	3.72
Openness	0.43	4.99	4.05	2.80	0.44	4.98	4.12	2.80	0.40	4.99	3.98	3.12

Note: All variables are in natural logs. PL stands for per labour.

Table 7A. Correlation Coefficients of the Variables in the GDP and TFP Regressions

OECD	PL GDP	PL Inv	Patents	Sec.School	Openness
PL GDP	1				
PL Inv	0.9744*	1			
Patents	0.5322*	0.5260*	1		
Secondary school	0.2311*	0.2212*	0.2041*	1	
Openness	0.4280*	0.5267*	0.0689	0.3412*	1
Non OECD	PL GDP	PL Inv	Patents	Sec.School	Openness
PL GDP	1				
PL Inv	0.9658*	1			
Patents	0.5976*	0.5959*	1		
Secondary school	0.6596*	0.6225*	0.4059*	1	
Openness	0.2595*	0.1969*	-0.1384*	0.3882*	1

Note: All variables are in natural logs. PL stands for per labour.